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ESSAY

Tried and true vs. shiny and new: Method switching in long-term aquatic datasets

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Scientific Significance Statement

Long-term datasets in aquatic science are important for detecting temporal changes, generating hypotheses regarding ecological phenomena, and understanding the effects of stressors on ecosystems. With rapid technological advances over recent decades, long-term data collection methodologies are continually refined, updated, and often completely switched. However, there is a shortage of discourse regarding the best practices in switching methods for long-term data collection in aquatic ecosystems. In this paper, we discuss factors that contribute to the successes and failures of method switches in long-term aquatic datasets. We present three case studies that demonstrate successful method switching and then outline best practices for maintaining data integrity during these transitions. Our goal is to initiate discussion among current and future managers of long-term aquatic monitoring programs to help guide decisions regarding method switching.

Long-term datasets are foundational resources in aquatic research, vital for establishing baselines and detecting shifts in aquatic biodiversity, water quality, and ecosystem function. For example, the Hawaii Ocean Time Series (HOTS), which has sampled biogeochemical data at Station Aloha in the North Pacific Subtropical Gyre since 1988, played a crucial role in documenting temporal variability in ocean carbon inventories and fluxes and provided the first evidence for a multi-decade decline in marine pH associated with climate change (Dore et al. 2009). Research from U.S. National Science Foundation Long Term Ecological Research sites has advanced understanding of ecosystem dynamics, including the long-term effects of invasive species on lakes (e.g., Walsh et al. 2016) and the influence of disturbances on watershed

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biogeochemical processes (e.g., Miniat et al. 2021). Finally, another NSF initiative, the Continuous Plankton Recorder surveys, are some of the longest-running aquatic long-term datasets, with one survey collecting data continuously since 1931 (www.cprsurvey.org). These surveys have demonstrated how climate change is affecting plankton communities.

The insights gained from such long-term datasets are only as robust as the data that have been collected. It is, therefore, a priority for those managing long-term datasets to ensure data quality. Advances in technology or sampling methods often leave researchers with a dilemma: switch to the newer method (i.e., "emerging" method) and take advantage of novel technologies, or continue with the older, existing method (i.e., "established" method) and maintain continuity in sampling protocol. Long-term dataset managers may choose to adopt emerging methods for many reasons: the emerging method could be faster, more efficient and/or more cost-effective, it might offer real-time data collection, or it could reveal previously unattainable or undetectable information. As a group of early career researchers, many of the authors of this essay have been in the position of taking responsibility for managing long-term aquatic datasets and have seen first-hand the importance of mindful data stewardship. Researchers commonly acknowledge the challenges associated with method switching in long-term monitoring programs. However, these discussions often occur informally between small groups of colleagues, not among the wider scientific community. As such, the literature lacks first-hand examples of how to proceed with adopting new methods. Here, our goal is to initiate broader discussion among current and future managers of long-term datasets in the aquatic sciences to help guide decisions about method switching. To achieve this, we discuss indicators of method-switching successes and failures. Then, we outline three case studies of method-switching successes in long-term datasets and suggest a set of best practices. We acknowledge that certain emerging methods produce data resembling those of the established methods but improve efficiency, speed, or cost-effectiveness, whereas other emerging methods generate entirely new data types. While the decision to begin collecting novel data types is worthy of discussion, we focus on the former.

Factors determining the success or failure of a method switch

A successful method switch in long-term data collection depends on two factors: (1) achieving the pre-established goals of the method switch and (2) ensuring that the data collected from both methods are comparable, thereby maintaining the dataset continuity. Thus, it is important for researchers to establish clear goals for a method switch and to follow well-defined best practices throughout the method switch to ensure continuity (*see* Section Best practices for method switching of this paper for best practices). As new technological advances enable the collection of data at increasingly finer resolutions, switching to methods that are faster, more efficient, or more cost-effective can be appealing to researchers managing long-term datasets. Researchers may have many reasons to switch methods. For example, the increased availability of remote sensors and autonomous vehicles provides researchers with significantly more real-time data than manual sampling methods, while reducing researcher time and increasing data throughput (Latifi et al. 2023). Furthermore, the rise of AI and machine learning has increased the amount of data that can be processed and information that can be obtained from a dataset (e.g., Fuchs et al. 2022; Kraft et al. 2022). In addition, emerging technologies can enable the collection of previously unattainable or undetectable data, for example, lowering detection limits (e.g., Leskinen et al. 2012) or using eDNA to monitor rare, cryptic, or invasive species (e.g., Barata et al. 2021). The long-term, collaborative nature of these datasets means that collection and management will be carried out by multiple generations of students, post docs, faculty, and government/agency scientists. The dynamic nature of such research teams means that establishing clear goals from inception and following best practices during the transition will aid in maintaining the integrity of long-term datasets during method switches.

Accordingly, method switching failures in long-term datasets usually occur when (1) the pre-established goal(s) are not met and/or (2) the data collected from the established and emerging method are not comparable, resulting in a discontinuous dataset. While not meeting a pre-established goal is often straightforward (e.g., financial or labor cost was not reduced, the detection limit was not lowered, etc.), discontinuous datasets will compromise one's ability to capture ecological insights but can occur for a variety of reasons. For example, what was measured previously and what the new method captures may be representative of the same ecological process but are not the same measurement (e.g., algal chlorophyll *a* vs. total cell biovolume; Ramaraj et al. 2013). Furthermore, as emerging technologies increase sample throughput through automation, the scale of data collection may change dramatically. This can make statistical comparison between the established and emerging methods challenging (Cutter 2013). Finally, switching to a method that lowers the limits of quantification or detection can sometimes be straightforward to account for. However, in other cases, this may complicate comparisons between old and new methods. While the collectors of such data may appreciate and understand these changes, long-term datasets often serve a variety of different end-users, making the ability to capture ecological insights increasingly difficult.

Due to the numerous challenges associated with method switches (Fig. 1), it can be difficult to define a method switch as a success or a failure; rather, outcomes exist on a continuum. For example, while a method switch might be

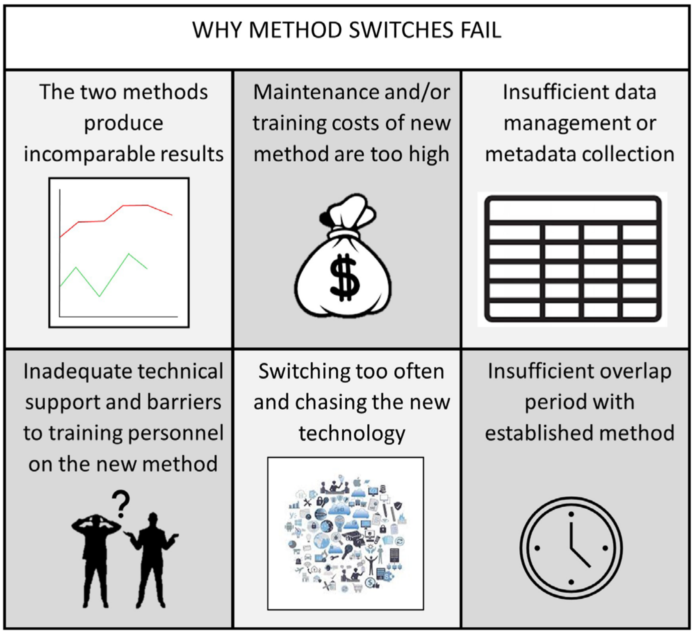

Fig. 1. Common reasons why method switches fail.

considered a "success" within its own long-term data collection program, it may pose challenges for other researchers aiming for methodological consistency between studies. Switching to more advanced technology might make it more difficult for other labs to replicate methodologies, reducing global access to and comparability among datasets. Furthermore, researchers may be motivated to repeatedly switch methods to capture the "best" data when a field is just establishing long-term datasets. Chasing "the best," unfortunately, can lead to delays in establishing datasets that would benefit policy and regulation. A prime example of this is micro- and nanoplastics pollution research, which suffers from a lack of continuous datasets despite a decade of widespread interest in the topic (Lusher and Primpke 2023). Given these nuanced challenges, there are often many reasons to avoid method switching altogether.

Three case studies on successful method switching

To highlight method-switching successes in long-term datasets, we present case studies that fall into three common categories of method switching: (1) manual-to-manual, (2) automated-to-automated switching, and (3) manual-to-automated. Here, "manual" refers to methods where the majority of the method, analysis, and interpretation is carried out by a person (e.g., measuring Secchi disk depth or cell counting with light microscopy). Conversely, "automated" refers to methods where most of the method, analysis, and interpretation is carried out by a machine or an automated process (e.g., satellite imaging or flow cytometry).

Manual-to-manual: A new method to increase the precision of fish age estimation

Long-term datasets characterizing fish age are essential for assessing and managing fish populations, studying life histories and responses to environmental change, and ensuring sustainable fisheries (e.g., Fergusson et al. 2018). The conventional method for fish aging is to collect fish otoliths, which feature incremental growth patterns—similar to tree rings (Campana 1999). Fish age can be determined by counting annual growth rings (Campana 1999), but environmental stressors and physiological factors can obscure these growth patterns, making visual aging challenging (Heimbrand et al. 2020). However, emerging methods, such as chemical aging based on otolith elements (e.g., magnesium, zinc, and phosphorus), can enhance precision: Heimbrand et al. (2020) found higher overall precision and percentage agreement among humans analyzing otolith images of Baltic Cod with chemical vs. visual makers. These findings demonstrate method switching success because (1) the researcher's goal of increasing precision in age estimate was fulfilled and (2) the data from both methods are comparable (Fig. 2A).

Automated-to-automated: Digitizing long-term aerial surveys

Aerial imaging surveys offer crucial data for long-term monitoring of the distribution and abundance of aquatic organisms. For example, the Chesapeake Bay Program (CBP) has employed aerial surveys to map the abundance and distribution of submerged aquatic vegetation in the Chesapeake Bay and its tributaries since 1984 (Orth et al. 2022). Although the CBP originally used a panchromatic camera for its surveys, in 2014, it introduced a digital mapping camera to incorporate emerging technology. By 2016, CBP had completely phased out the film. This case study demonstrates a method switching success because (1) it fulfilled the researchers' goals of eliminating a data processing step, increasing picture resolution, and increasing spatial accuracy (Orth et al. 2022) and (2) data from the film (established) and digital (emerging) methods are comparable (Fig. 2B), allowing for a continuous dataset.

Manual-to-automated: Toward near-real-time phytoplankton community monitoring

Understanding phytoplankton community dynamics is important for assessing ecosystem health, addressing climate change impacts, protecting water quality, and guiding management efforts. Traditionally, researchers have assessed phytoplankton community composition using light microscopy, which involves time-consuming sample preparation and visual identification. Recognizing the labor intensity of this approach, the benefits of the recent development of automated observing technologies are clear (Muller-Karger et al. 2018). Imaging flow cytometry is a commonly explored technique as an alternative to manual cell counting (Owen et al. 2022). This automated method combines the high-

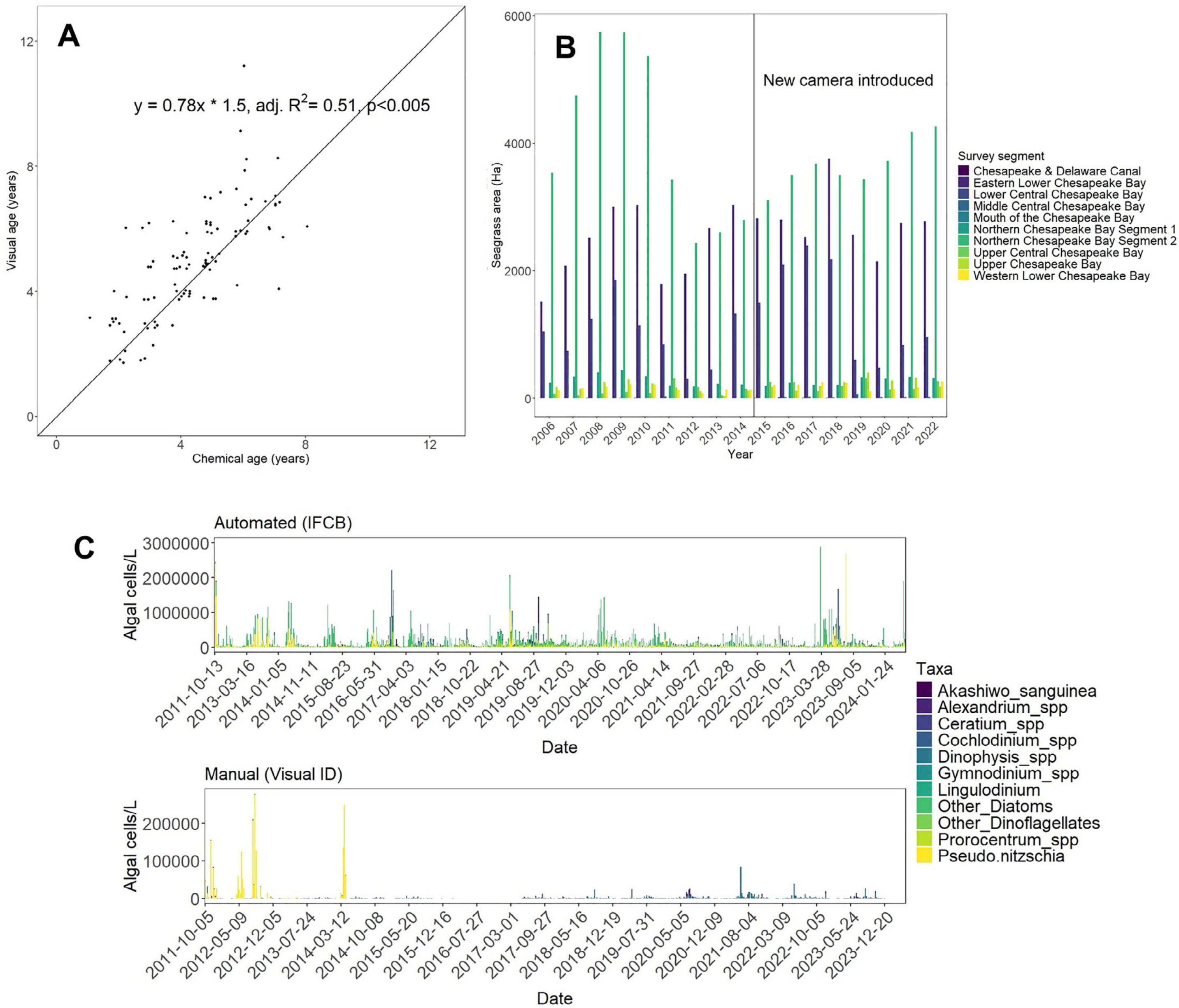

Fig. 2. Examples of best practices for method switching. (**A**) Compare the two methods. Data from Heimbrand et al. (2020). (**B**) Make method switch explicit on graphs. Data from Virginia Institute of Marine Science SAV monitoring and restoration program (http://www.vims.edu/bio/sav). (**C**) Include an overlap period. Data from the IFCB104 station at Santa Cruz Municipal Wharf, California Ocean Observing Data Systems Portal—CalHABMAP (https://data.caloos.org).

event-rate capability of flow cytometry with the benefits of single-cell image capture, generating tens of thousands of phytoplankton images per hour. Together with machine learning, flow cytometry can enable near-real-time monitoring of in situ phytoplankton communities by automatically classifying images (Fuchs et al. 2022). This case study demonstrates a successful method switch because it fulfilled the researchers' goal of reducing person-hours. Although there are discrepancies between data collected using the manual counting (established) and the flow cytometry/machine learning (emerging) methods (Fig. 2C), the researchers have implemented a multiyear overlap period of methodologies, which allows end data users to implement their own calibration methods depending on the application (e.g., Fischer et al. 2020).

Best practices for method switching

1. *Consider the type of method switch and establish goals*—Determine the broad type of method switch (i.e., manual-to-

manual, manual-to-automated, or automated-to-automated) and research potential pitfalls associated with that type of switch. Consider changes in cost-per-datum. Establish clear goals for the method switch (Fig. 3).

2. *Create a plan*—Ensure there is a robust plan in place for implementing the emerging method. Plans might include creating new standard operating procedures, planning a pilot program for the emerging method, and/or determining overlap time between the two methods. This should also include a data management plan, covering considerations such as quality assurance and quality control (QA/QC), updating of algorithms, updating of published methods, making the switch clear in metadata, and so forth.
3. *Compare data collected from both methods*—Before fully transitioning, statistically compare data collected from both approaches. The comparison should consider: (1) Are there differences in the results between the two methods? (2) If so, what are these differences and are they consistent? (3) Are the datasets and metadata comparable between the two methods? (4) What are potential explanations for differences? (5) How do the outcomes of data QA/QC compare? (6) Did the switch meet pre-established goals?
4. *Consider involving other research groups in intercalibration studies*—You will likely not be the only group considering switching to the novel method. Intercalibration studies, like the GEOTRACES (Cutter 2013) program for ocean biogeochemistry, involve the sharing of data between laboratories to achieve the lowest systematic and random errors and maximize the precision and accuracy of analytical methods.
5. *Maintain an active dialogue and continuously revisit the decision to proceed with the method switch*—After statistically comparing methods, consider the advantages and disadvantages of keeping the established method vs. switching to the emerging method. Have an open conversation with collaborators about how to move forward with the switch: proceed, do not proceed, or continue with both methods concurrently. Consider the longevity of the approach and

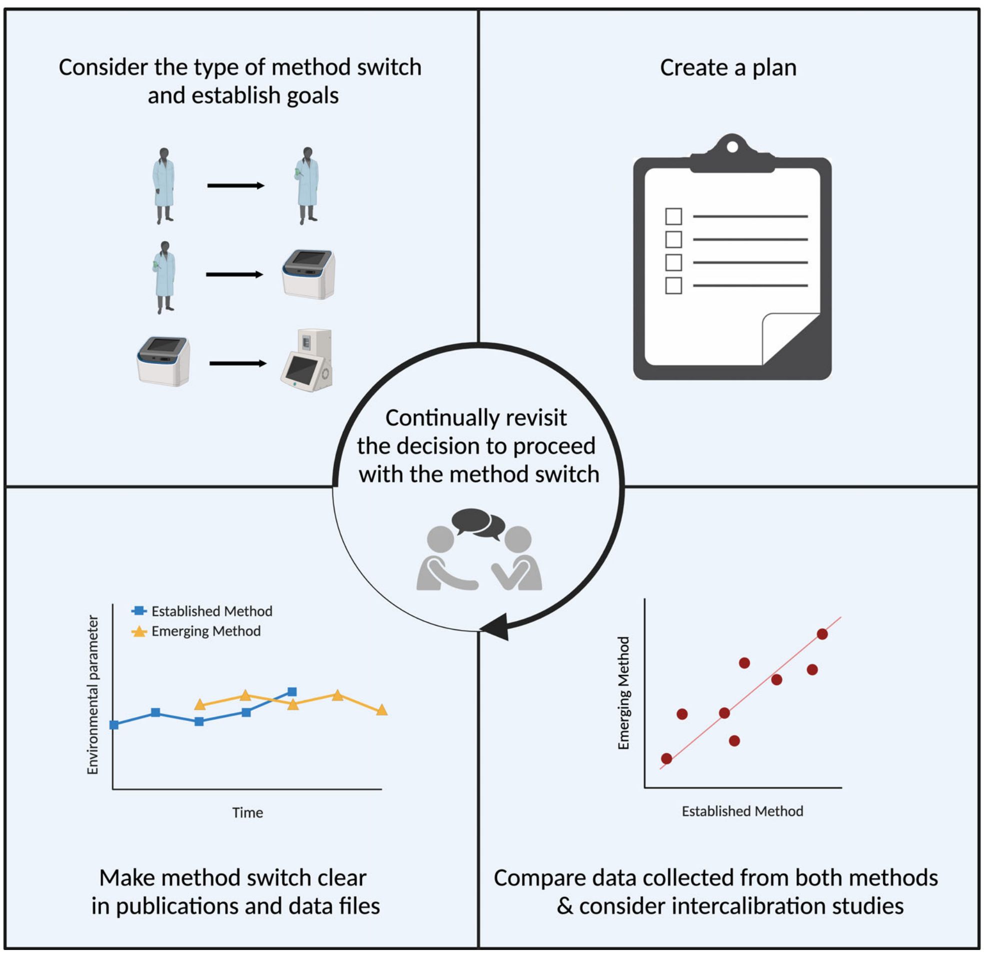

Fig. 3. Conceptual diagram for best practices for method switching in the aquatic sciences. Created with BioRender.com.

financial barriers to the emerging method if other research groups are gathering congruous datasets. Finally, maintain flexibility when defining the switch as a success or failure if the original end goals have not been met. For example, if data from a new method to improve detection limit cannot be properly inter-calibrated with the existing long-term data due to many zeros produced by the older method, consider the advantages of the additional insight provided by the new method when deciding whether the method switch has failed.

6. *Make method switches clear in publications and datafiles*—Make the method switch clear in downstream applications by describing both methodologies thoroughly and explaining the rationale behind the switch, explicitly showing the switch in figures (Fig. 2C), and discussing the implications of the method switch, including guidance on how to address the method switch when analyzing long term trends (e.g., were detection limits or SI units changed? How were the two datasets aggregated for analysis?). Finally, if data are publicly available, all details about the method switch and its effects on end-user interpretation should be provided in metadata and a README guide file following FAIR Data Principles, which promote the conscientious management and stewardship of digital scientific data by improving its Findability, Accessibility, Interpretability, and Reuse (Wilkinson et al. 2016).

Conclusion

Long-term aquatic datasets provide invaluable insights. However, maintaining their integrity amidst evolving methodologies poses challenges. This raises two considerations for dataset managers: whether to adopt emerging methodologies or maintain established techniques and how to ensure data integrity during a method transition. While the decision to switch methods is case-specific, our paper addresses the critical need for structured discussions on such switches and the development of standardized guidelines for transparent data reporting. With the aquatic sciences trending toward increasingly collaborative, interdisciplinary research that employs automated data collection methods and Big Data (Durden et al. 2017), dataset managers must deliberate on adapting their data collection methods to ensure continuous and effective monitoring of Earth's ecosystems.

Author Contributions

Catriona L. C. Jones and Kelsey J. Solomon co-led the entire manuscript effort, contributing equally, and created the graphics. All authors contributed to the conceptualization of the essay topic and the writing and editing of the manuscript.

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